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Crop Advisor: Intelligent Crop Recommendation System

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ABSTRACT

Agriculture plays a vital role in India's economic landscape, supporting millions of livelihoods and significantly contributing to the country's financial stability. By 2024, it is estimated that the agricultural sector will account for approximately 18-20% of the nation’s GDP while providing employment to nearly half of its population. Moreover, it remains a critical factor in ensuring food security for over 1.4 billion citizens. Despite its importance, crop productivity per hectare remains below global standards, contributing to economic distress and financial instability among farmers. To address this challenge, this study introduces an intelligent crop regulation framework powered by machine learning. The proposed system gathers essential agricultural data, including historical and present crop yields, meteorological patterns, soil characteristics, and fertilizer application rates. By leveraging predictive analytics, it assesses potential weather fluctuations, expected rainfall, and disease susceptibility, allowing farmers to estimate yield projections even before cultivation begins. Additionally, the framework integrates real-time market variables such as cultivated land area, trade statistics, consumer behavior trends, and past pricing records. Through comprehensive data analysis, the system forecasts market demand and expected yields for different crops. A variety of machine learning models are employed to enhance decision-making. Regression-based methods, including Random Forest (RF), Support Vector Machine (SVM), and Multiple Linear Regression (MLR), contribute to yield estimation. Classification techniques, such as K-Nearest Neighbors (KNN), provide insights into crop selection and performance. Furthermore, time-series forecasting models like AutoRegressive Integrated Moving Average (ARIMA) and optimization algorithms such as Genetic Algorithms (GAs) facilitate precise market demand assessments. The integration of these advanced predictive techniques equips farmers with informed recommendations, ensuring optimal crop selection and resource allocation to enhance profitability and sustainability.

Keywords Crop Forecasting, Market Demand Prediction, Machine Learning Models, Random Forest (RF), Support Vector Machine (SVM), Multiple Linear Regression (MLR), K-Nearest Neighbors (KNN), AutoRegressive Integrated Moving Average (ARIMA), Time-Series Analysis, Genetic Algorithms (GAs), Agricultural Decision Support.

INTRODUCTION

Agriculture has been a fundamental pillar of India’s economy, contributing approximately 18-20% of the country’s Gross Domestic Product (GDP) and serving as a primary source of employment for nearly half of the population. With a long and rich history in farming, India remains one of the largest producers of agricultural goods worldwide. This sector is essential for supporting millions of farmers and ensuring food security for over 1.4 billion people.

Despite its significance, Indian agriculture faces numerous challenges, including climate change, unpredictable weather patterns, and market fluctuations. Factors such as rising temperatures, erratic rainfall, and extreme weather conditions create obstacles in crop production, making it difficult for farmers to achieve stable yields. The ability to predict crop yield and market demand is critical for effective decision-making, as it allows farmers to plan their cultivation strategies efficiently. However, traditional methods of predicting these factors are often unreliable, leading to financial losses and increased risks.

Market demand forecasting involves analyzing various parameters, including current market trends, cultivated land, trade statistics, retail pricing, and consumer preferences. Similarly, predicting crop yield is complex, as it depends on multiple variables such as soil quality, climate conditions, pest infestations, and agricultural practices. Farmers traditionally rely on experience and intuition to estimate yields, but this approach does not always yield accurate results. A lack of reliable data can make it challenging for them to determine the best crops to plant, optimal sowing times, and suitable fertilizer applications. Moreover, uncertainty in weather conditions further complicates agricultural planning, often leading to economic distress.

Advancements in technology, particularly machine learning, offer a solution to these challenges. By utilizing historical data and real-time information, predictive models can provide accurate insights into market demand and crop yield

before the sowing process begins. A comprehensive system that integrates past and present agricultural data can assist farmers in selecting the most profitable crops while minimizing risks. This system can analyze factors such as rainfall, temperature, and soil composition to forecast yield, helping farmers maximize productivity and profitability.

This research proposes the development of a market demand analysis model that evaluates key agricultural and economic factors to provide farmers with real-time insights. Additionally, a crop yield prediction framework will be designed to analyze historical data and environmental influences to enhance agricultural decision-making. By leveraging data-driven techniques, the proposed system will empower farmers with accurate predictions, ensuring better planning and resource management.

In conclusion, the need for an intelligent and reliable crop forecasting system is greater than ever. By harnessing machine learning techniques, this research aims to create a user-friendly platform that assists farmers in predicting crop yields, selecting the best planting times, and optimizing fertilizer use. Implementing such a system can significantly improve agricultural sustainability, enhance food security, and contribute to economic stability in India.

RELATED WORK

Improving agriculture increasingly relies on integrating technology and innovative tools to make farming more efficient and manageable [4]. One approach involves using machine learning (ML) to forecast the most suitable crops to cultivate. This paper explores various ML methods, such as K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Multiple Linear Regression (MLR) and Random Forest detailing how each contributes to more informed farming decisions and deep learning (DL) methods, such as AutoRegressive Integrated Moving Average (ARIMA), Genetics Algorithms (GAs). However, a major challenge lies in adapting these technologies to process real-time data from markets and farms effectively [5].

An early project created a website to study how weather affects crop production in certain districts of Maharashtra [10]. The districts were chosen based on the types of crops grown there. The topmost district with the largest crop areas was selected for the study. The crop chosen for the study is Tomato, as these are commonly grown in the area. The project looked at crop yields over 3 years. The model developed to predict the yields was fairly accurate, with accuracy ranging from 90% to 98%, and an average accuracy of 93%.

Significant efforts and numerous machine learning (ML) algorithms have been applied within the agriculture sector to address pressing challenges. One of the primary objectives in agriculture is to boost farm productivity while delivering produce to consumers at optimal prices and quality. However, statistics reveal that around half of farm produce goes to waste and fails to reach the consumer. The proposed model aims to address this issue by implementing methods to minimize post-harvest losses, ensuring more efficient distribution and reducing wastage in the supply chain [11].

Firstly, for market demand analysis, we utilize the AutoRegressive Integrated Moving Average (ARIMA) algorithm. ARIMA is highly effective for analyzing and forecasting trends based on historical and time-dependent data. It processes real-time inputs such as current market trends, sowed land under a crop, import/export statistics, retail data, and consumer data to predict future market demand accurately. Additionally, it incorporates seasonal variations, helping identify recurring patterns in demand across different times of the year. With an accuracy of 93%, ARIMA provides valuable insights to assist farmers in aligning their crop production with future market needs.

To further enhance market demand analysis, we explored other algorithms like Genetics Algorithms (GAs), and Long Short- Term Memory (LSTM). These algorithms effectively analyze complex relationships and classify market dynamics based on high-dimensional data [9]. While all these methods offer accuracy above 90%, ARIMA stands out due to its ability to model temporal patterns and integrate seasonal effects, making it the most suitable choice for market demand forecasting in agriculture.

Secondly, we use the Regression Forest (RF) algorithm for crop yield prediction before sowing the Crop. The prediction model takes input data, including cropland area (in acres), season, soil quality, fertilizer usage, crop rotation, variable plant variety, intercropping, last year's yield, and the yield from the year before last. Additionally, rainfall, weather impact, and disease effects are predicted using APIs and integrated into the model for more accurate predictions.

After processing this input data, the Regression Forest model achieves an outstanding accuracy of 99%. We also explored other algorithms like K-Nearest Neighbors (KNN), Artificial Neural Networks (ANN), Multiple Linear Regression (MLR), and Support Vector Machines (SVM). While all these algorithms provided accuracy above 95%, Regression Forest outperformed them, making it the best choice for crop yield prediction.

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Then, to minimize wastage, we use the Regression Forest (RF) algorithm to help farmers decide whether to sow a crop. This algorithm analyzes factors like market demand and predicted crop yield to ensure the decision aligns with market needs. It effectively handles complex relationships between various factors like Market demand and predicted crop yield while identifying and prioritizing the most critical ones influencing yield and profitability. If the expected yield meets demand, it recommends sowing; otherwise, it advises against it, avoiding overproduction. With an accuracy of 98%, Regression Forest is a highly effective tool for guiding farmers in making informed decisions.

Example:
In our market demand analysis system, we employ the AutoRegressive Integrated Moving Average (ARIMA) algorithm, which is effective for time-series forecasting. ARIMA consists of three components: the Autoregressive (AR) term, which captures dependencies on past market demand values; the Differencing (I) term, ensuring stationarity by removing trends or seasonal effects; and the Moving Average (MA) term, which accounts for past error terms. It also includes external factors such as market trends, sowed land area, import/export data, retail, and consumer data, represented as coefficients to improve predictions.

The general formula for market demand prediction using ARIMA is:

1. Market Demand=β0+i=1∑pβi·Market Demandt−i
+j=1∑qθj·ϵt−j+k=1∑mαk·Xk+ϵt

This model forecasts market demand with 93% accuracy, aligning crop production with anticipated demand.

For crop yield prediction, the Regression Forest (RF) algorithm is used, analyzing factors like cropland area, season, soil quality, fertilizer usage, crop rotation, variable plant variety, intercropping, last year's yield, and year-before-last yield. Additionally, predicted values for rainfall, weather impact, and disease effects are used. The general formula for crop yield prediction is:

Crop Yield= F (Cropland, Season, Soil Quality, Fertilizer Usage, Crop Rotation, Variable Plant Variety, Intercrop, Last Year Yield, Year Before Last Yield, Predicted Rainfall, Predicted Weather Impact, Predicted Disease Effect)

The RF model predicts crop yields with 99% accuracy. The Decision Support System (DSS) integrates market demand and predicted crop yield. The system recommends sowing a crop only if the predicted yield meets or exceeds market demand, preventing overproduction. The decision rule is:

1. If Predicted Yield ≥ Market Demand, recommend sowing ("Sow").
2. If Predicted Yield < Market Demand, advise against sowing ("Do not Sow").

Combining ARIMA for market demand analysis and Regression Forest for crop yield prediction offers a data-driven, efficient approach to crop recommendation, enhancing sustainability and profitability for farmers.

This integrated system ensures crops are aligned with market needs, optimizing production, and minimizing waste.

MODEL AND METHODOLOGIES

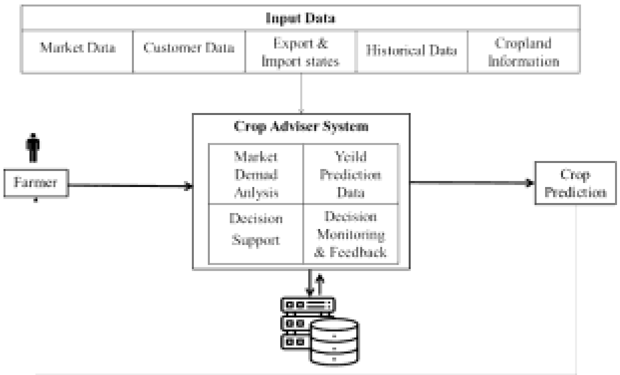
While agricultural technology has advanced significantly, developing a user-friendly system for crop recommendation remains a challenge. This proposal aims to address these gaps by creating an intuitive platform that analyzes key agricultural factors, including rainfall patterns, weather conditions, soil health, fertilizer usage, disease risks, crop rotation strategies, plant variety selection, intercropping methods, and historical yield data. Additionally, market dynamics such as cultivated land distribution, trade patterns, retail pricing, and consumer demand are integrated into the system. The primary goal is to forecast market demand and estimate crop yields before planting, enabling farmers to make well-informed decisions based on seasonal trends. By optimizing crop selection, this approach helps prevent overproduction, reduce shortages, and enhance the financial stability of farmers.

The proposed model focuses on predicting market demand and crop yields for a specific crop in the Maharashtra region. By integrating agriculture with advanced data analysis techniques, this approach enhances farming practices by regulating yield levels and ensuring efficient resource utilization. Historical data plays a crucial role in these predictions, as it helps identify patterns and trends that influence current agricultural outcomes.

To analyze market demand, the system processes key data points such as current market trends, cultivated land distribution, trade activity, retail sales, and consumer behavior. For crop yield forecasting, the model evaluates factors like precipitation, temperature variations, soil characteristics, fertilizer usage, disease resistance, crop rotation methods,

plant variety, and intercropping strategies. Additionally, information on soil classification by region, along with weather patterns such as temperature fluctuations and average rainfall, is incorporated into the dataset.

The collected data undergoes cleaning and preprocessing to ensure accuracy and consistency. Missing values are replaced using statistical methods, while categorical data is transformed into numerical representations. One-hot encoding is applied to effectively process categorical variables before inputting the dataset into the predictive model. This systematic approach enhances the precision of market demand and crop yield forecasts, enabling farmers to make data-driven decisions for improved agricultural outcomes.



[Fig.1: System Architecture]

Figure 1 shows the system architecture for a proposed crop recommendation system, designed as a mobile application with three primary modules: Market demand analysis Module, Crop yield prediction and Decision Support Module.

1. Input Data:

a. Market Demand Analysis:

i. Current market data
ii. Sowed land data
iii. Import/Export data
iv. Retail data
v. Consumer data

b. Crop Yield Prediction

i. Season
ii. Disease Effect
iii. Rainfall
iv. Crop Rotation
v. Weather Impact
vi. Variable Plant Variety
vii. Soil Quality
viii. Intercrop
ix. Fertilizer Usage
x. Last Year's Crop Yield

c. Decision Support

i. Market demand
ii. Predicted Crop Yield

Mobile Application: The model operates as a mobile app, where farmers must first register through a registration process. Once registered, they gain access to the app's features.

Overall, the system is designed to support farmers by making data-driven predictions and recommendations, thus helping them analyze market demand regulate crop yield according to it and manage resources more effectively.

The user interface for the proposed system is designed using the Ionic Framework, incorporating JavaScript, AngularJS, and ReactJS. This approach allows for seamless deployment across multiple platforms, including iOS, Android, desktop, and web, as a Progressive Web Application, all managed within a unified codebase.

To store and manage essential datasets, the system utilizes Firebase as a cloud-based database solution. Machine learning techniques are employed to analyze market demand and forecast crop yields by identifying patterns and correlations within the data. The model is trained using historical records, enabling it to recognize trends and generate reliable predictions. Various machine learning algorithms are evaluated for accuracy, with Random Forest regression and time-series forecasting models demonstrating the best performance. The model leverages multiple decision trees to improve prediction stability, ensuring precise market demand analysis and crop yield forecasts.

RESULTS AND DISCUSSION

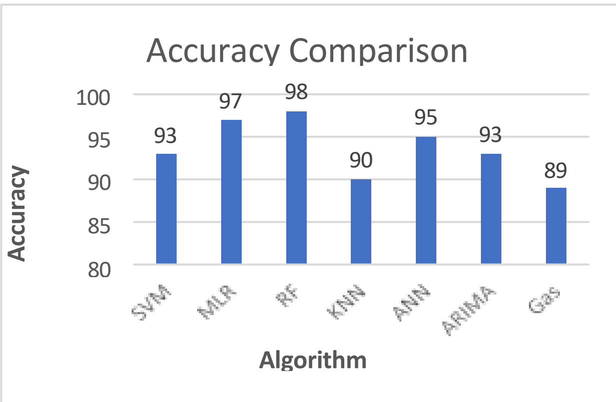
This section presents the results obtained from applying various machine learning algorithms to agricultural data specific to the Maharashtra region. The dataset includes key parameters such as cultivated land area, retail market trends, trade statistics, consumer demand, and farmer-reported data on rainfall, weather conditions, soil characteristics, fertilizer usage, disease impact, crop rotation patterns, plant variety selection, intercropping, and previous two years' yield records.

The accuracy of the crop yield forecasts and market demand predictions generated by different algorithms is assessed and compared. Among the tested models, the Random Forest algorithm demonstrated the highest prediction accuracy at 99%, while the ARIMA model achieved an accuracy of 93%.

The machine learning techniques used for crop yield prediction include Artificial Neural Networks (ANN), Support Vector Machines (SVM), Multivariate Linear Regression, Random Forest, and K-Nearest Neighbors (KNN). For market demand analysis, time-series models such as ARIMA and optimization techniques like Genetic Algorithms (GAs) were utilized. A comparative accuracy summary of these algorithms is presented in Table 1, with a visual representation provided in Figure 2.

Table 1: Accuracy vs Algorithm

Algorithm	Accuracy (%)
Support Vector Machine (SVM)	93
Multivariate Linear Regression (MLR)	97
Random Forest (RF)	98
K-Nearest Neighbor (KNN)	90
ANN	95
ARIMA	93
Genetics Algorithms (GAs)	89



[Fig. 2: Accuracy VS Algorithm]

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IMPLEMENTATION & RESULTS

User Input Fields:

- **Crop Type:** The user has selected "Tomato" as the crop.
- **Land Area:** Entered a "value" (likely in acres or hectares).
- **Season:** Set to "Summer/Monsoon/Winter"
- **Rainfall, Fertilizer Usage, Weather Impact, Disease Effect:** All set to "Low/High"
- **Soil Quality:** Set to "Bad/Good"
- **Crop Rotation & Intercropping:** Both selected as "Yes/No"
- **Variable Plant Variety:** Marked as "Yes/No"
- **Previous Yield Data:**
- **Last Year Yield:** Entered a "value"
- **Year Before Last Yield:** Also entered a ""value

Predicted Crop Yield:

- The result box displays a numerical value, which represents the expected crop yield.
- This value is likely derived from a machine learning model that processes agricultural parameters.

Harvesting Time Market Demand Check:

- Below the prediction result, there is an option to **"Check Harvesting Time Market Demand."**
- Clicking the **"Check"** button will likely direct the user to another page that provides insights into market demand for the crop at harvest time.

Predicted Market Demand:

The result displayed in the text box is a value, which represents the estimated market demand for the selected crop.

- This prediction is likely generated using a machine learning model, such as the **Temporal Fusion Transformer (TFT)**, which analyzes historical market trends and external factors.

Decision Analysis Feature:

- Below the demand prediction, there is an option to **"Make Decision Analysis."**
- Clicking the **"Check"** button will likely take the user to another page where decision support tools help determine the best actions based on predicted demand.

Crop Yield and Market Demand Predictions:

- The **Crop Yield Prediction** field displays a value , which represents the estimated yield based on environmental and agricultural factors.
- The **Market Demand Prediction** field shows a value, indicating the projected market demand for the crop at harvest time.

Analysis Feature:

- Clicking the **"Analyse"** button processes the provided yield and demand values to generate an insightful recommendation.
- The analysis result is displayed below, stating:
  ■ "You can sow and gain profit because there is good market demand."
- This suggests that based on the high demand and predicted yield, it is a favourable time to cultivate and sell the crop for maximum profit.

Feedback Option:

- A **"Feedback"** button is present, likely allowing users to share their thoughts on the analysis or the system's accuracy.

Feedback Form Fields:

- **Date:** Displays, indicating when the feedback is being submitted.
- **Sowed Land:** A dropdown or input field showing the value **2**, representing the amount of land (likely in acres or hectares) used for sowing crops.
- **Expected Crop Yield:** Shows value, which is the predicted crop output based on the entered sowed land and other relevant factors.

Submit Button:

- The blue **"Submit"** button allows users to send their feedback, likely storing the data in a database for future reference or model improvement.

FUTURE SCOPE

Expansion of Crop Variety Analysis

The model can be expanded to support a wider range of crops, including region-specific and high-value commercial crops. By integrating additional datasets related to soil fertility, climate adaptability, and genetic modifications, the system can cater to diverse agricultural needs.

Climate Change Adaptation

With growing concerns over climate change, the model can be adapted to simulate different climate scenarios and recommend resilient crop varieties. By forecasting the long- term impact of changing weather patterns, the system can help farmers implement climate-smart agricultural practices.

Mobile and Voice-Assisted Applications

To ensure accessibility for farmers with limited technological expertise, the system can be deployed as a mobile-friendly application with multilingual support and voice-based assistance. This would enhance usability and encourage widespread adoption.

Supply Chain Optimization

The framework can be extended to optimize logistics and transportation networks, ensuring efficient distribution of agricultural produce. By predicting demand patterns and monitoring inventory levels, wastage can be minimized, and food supply chains can be strengthened.

Personalized Crop Selection Based on Soil and Climate Conditions

The model can be tailored to provide personalized crop recommendations based on region-specific soil and climate conditions. By analyzing historical data, the system can suggest the best crops for each season to maximize yield potential.

Automated Smart Irrigation

Machine learning can be utilized to develop automated irrigation systems that optimize water usage based on real- time soil conditions, weather forecasts, and crop requirements. This will contribute to water conservation and prevent over-irrigation.

CONCLUSION

This study introduces an integrated machine learning-based system for crop yield prediction and market demand analysis aimed at supporting farmers in making data-driven decisions. Agriculture plays a crucial role in the economy, and accurate forecasting is vital for ensuring food security and optimizing production. The proposed system utilizes various inputs, including cropland area, season, soil quality, fertilizer usage, crop rotation, and historical yield data, along with real-time predictions of rainfall, weather impact, and disease effects, to offer reliable crop yield predictions.

For market demand analysis, the system uses data such as current market trends, sowed land under a crop, import/export statistics, retail data, and consumer data. The AutoRegressive Integrated Moving Average (ARIMA) model processes these data points to predict future market demand with 93% accuracy. This data-driven approach enables farmers to adjust their crop production to meet market needs effectively.

Among the various machine learning models evaluated for crop yield prediction, including K-Nearest Neighbors (KNN), Artificial Neural Networks (ANN), Multiple Linear Regression (MLR), and Support Vector Machines (SVM), the Random Forest (RF) algorithm delivered the highest accuracy, reaching 99%.

The decision support system, powered by the Regression Forest (RF) model for crop yield prediction and the ARIMA model for market demand analysis, recommends whether a farmer should sow a particular crop based on the predicted yield and forecasted market demand. By analyzing market demand and predicted yield, the system advises against sowing if the predicted yield exceeds market demand, preventing overproduction and ensuring profitability.

This integrated approach represents a significant step toward addressing key agricultural challenges such as fluctuating market demand and unpredictable environmental conditions. Future advancements may focus on incorporating additional external data sources, improving real-time prediction models, and extending the system to mobile platforms

for broader accessibility. Ultimately, this system has the potential to significantly improve agricultural productivity and stability, providing valuable support to farmers in meeting both market needs and sustainability goals.

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